The role of task switching costs in the selection of attentional control strategies

Undergraduate Research Thesis

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by

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Abstract

When performing visual search, such as looking for a friend in a crowd, there are many search strategies one can employ. Recent work has shown people often use suboptimal strategies, although there are vast individual differences for such choices. Why might this be so? Here, we considered the impact of updating – i.e., task switching – on attentional strategy choice. In the real world, we rarely perform the same search multiple times in a row; we tend to move from one task to the next. Thus, optimal performance demands we update strategies frequently. Moreover, people vary considerably in task switching abilities. In this experiment we looked at the relationship between task switching performance and visual search strategy. Participants performed the Adaptive Choice Visual Search (ACVS; Irons & Leber, 2018), where they viewed a display of red, blue, and green squares for target digits. A red and a blue target were presented on each trial and participants were free to report either target. The ratio of red to blue squares changed across trials, and the optimal strategy was to look through the smaller color subset. We set run lengths, or the number of trials in a row the optimal target was a particular color, to 1 and 3 for entire blocks. In a separate block of single-target visual search, we measured switch costs (RT on "switch" trials minus RT on "repeat" trials). We hypothesized that switch costs would relate to one's willingness to update strategies and thus predict search optimality – especially at the 1-run blocks. Results revealed no easily discernable relationship between switch costs and optimality. These results show that metrics related to task switching ability may not underlie visual search strategy. We speculate that subjective effort of strategy updating – rather than actual costs of such updating – may determine strategy use.

Introduction

Imagine you are standing in a crowded area filled with people as you search for a friend. You know that they are wearing a red shirt, so maybe the best strategy you could employ is to base your search for them on color. However, what if you were at an Ohio State football game and everyone is wearing red? This strategy to search the crowd based on color is no longer very efficient. What if your friend is very tall? You now might attempt to base your search on height features instead of color features to be more effective. The most efficient, or optimal, strategy tends to depend on the features of the surrounding environment and changes as the environment does. The optimal strategy can substantially improve performance (e.g., via shorter reaction time and higher accuracy), but many times people fail to use it (Bacon & Egeth, 1994).

Why do people choose not to use the optimal strategy? Here, we consider how one's ability might guide their choices. Despite people having impressive abilities to allocate their attention through goal-directed attentional control (e.g., Green & Anderson, 1956; Folk, Remington, & Johnston, 1992), individuals vary in their cognitive abilities, and this variation could impact strategy choice. We investigate this idea in the present paper.

In previous studies in our lab, we have found evidence that people avoid using optimal strategies because of the subjective effort associated with such strategies (Irons & Leber, 2016, 2018a). In order to optimize performance, people need to keep task goals in mind and seize control of their cognitive faculties accordingly (Braver 2012; Braver, Gray, & Burgess, 2007), which may be taxing. Additionally, optimality requires people to monitor their own performance, making judgements about the effectiveness of their current strategies relative to the overall goal (Cain, Vul, Clark, & Mitroff, 2012; O'Leary & Sloutsky, 2017; Wolfe 2013). This conflict-monitoring (and potentially updating of strategies) is also thought to be effortful (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Lorist, Boksem, & Ridderinkhof, 2005).

One further reason why monitoring the environment and one's own performance is cognitively demanding is that it often requires switching strategies and behaviors in order to remain optimal. This kind of task switching is a behavior that is perceived to be effortful and tends to be avoided (Arrington & Logan, 2004). Arrington and Logan asked participants to perform one of two judgement tasks about a digit. The participants were free to choose which one of these tasks they completed, but were asked to do each task about half of the time. Their results showed that alternating between the two tasks had slower reaction times than repeating the same task, indicating a switch cost. Additionally, participants had a probability of 0.678 of repeating the same task . The researchers hypothesized that having an inclination to repeat a task rather than switch to a different one could be due to wanting to avoid the cost of switching from one task to another (a perseveration bias). Additionally, Kool and Botvinick looked at the effects of "low-demand" versus "high-demand" task-switching on a participant's choice (Kool & Botvinick, 2010). In their task, participants were presented with two decks of cards and were told to select whichever deck they wanted on each trial. Once selected, participants were prompted to do one of two judgement tasks on a digit, depending on the digit's color. The high demand deck switched the judgement task being performed more frequently than the low demand deck, but participants were not told this explicitly. Their data showed that participants tended to pick the deck with less task switching, indicating an avoidance of cognitive effort.

While much of the work reviewed above focuses on subjective cognitive effort, here we entertain the notion that the avoidance of subjective effort may not alone explain strategy choice. Consider that effort and ability may sometimes be conflated. That is, individuals with greater abilities to perform a cognitive operation may find them to be less subjectively effortful and thus may be less likely to avoid these cognitive operations.

This project was designed to examine how ability metrics relate to strategy choice. Specifically, we used the Adaptive Choice Visual Search (ACVS) paradigm to study the relationship between task switching ability (assessed via switch costs) and attentional strategy choice (Irons & Leber, 2016, 2018a). In the ACVS, participants are presented with a display of colored squares containing digits inside of them. There are two targets on every trial: a blue square and a red square. Participants are only required to find one of the two targets on each trial and they are free to choose which one they want to search for. On any given trial there are more colored squares of one target color compared to the other; therefore, searching for the target square from the smaller colored subset is faster, as there are fewer squares of that color to look through (making this the *optimal target*). The optimal target color is switched over the trials, requiring participants to update their control settings if they wish to search for the optimal target. This paradigm emphasizes a distinction in target choice (an optimal versus a non-optimal target), allows us to characterize their attentional strategy use in the experiment, and requires switching between cognitive control settings in order to perform optimally.

Previous versions of ACVS have attempted to find a relationship between optimality and switch cost. We theorized that participants with poorer task switching abilities – reflected via a larger switch cost – would not search for the optimal target as often. This is because greater costs of switching work against any benefits in search speed when choosing the optimal target (Irons & Leber, 2019). However, the switch cost failed to relate to a strategy choice in our previous studies. In considering this failure to find a relationship, we speculated that our previous work did not contain a wide enough range of switch costs among our participants. Moreover, previous implementations of our paradigm incorporated relatively infrequent switching; therefore, the prospect of avoiding task switching – and its associated costs – might not have strongly impacted participants' likelihood to use the optimal strategy. We reasoned that a broader range of switch cost would need to be evaluated to potentially reveal a link.

In this study, we once again measured the relationship between switch cost and use of the optimal strategy in ACVS. We defined switch cost as how much slower a participant is in responding when they choose the target from the opposite color subset versus the same color subset, relative to the response color in the previous trial. In other words, switch cost is the reaction time on a "switch" trial minus their reaction time on a "repeat" trial, which we independently assessed via a forced-switching version of the ACVS. We expected that varying the run length, or the number of trials in a row a particular color is the optimal target, would affect the proportion of optimal choices that participants made. Specifically, we expected poorer optimality when the optimal color switches more frequently (i.e., shorter run lengths) compared to when less switching is necessary (i.e., longer run lengths). This is because, if a person were to maintain an optimal strategy, they would have to switch which subset they look through for the optimal target more frequently for shorter run lengths. Therefore, we expect to see participants use the optimal strategy less on blocks with shorter run lengths compared to those with longer run lengths.

Critically, we predict individual differences in strategy usage, such that individuals with a higher switch cost in the forced-switching task – i.e., poorer task switching ability – will perform less optimally at the ACVS task. Alternatively, if task switching ability is not an influential factor in optimal performance, then individuals' task switching costs should not relate to their optimality. The present experiment is designed to distinguish among these alternatives.

Methods

Participants

We ran 57 participants (37 Female, 13 Male) with an age range 18 – 33 years old. Seven participants were excluded for low accuracy (< 91.50%; three standard deviations below mean accuracy), giving us 50 viable participants. This sample size provides 90% power to reliably detect Pearson correlation coefficients of $r = 0.42$. These participants were recruited via the Ohio State Research Experience Program, which is a pool of undergraduate students taking an introductory psychology course. Each participant stayed for a 1-hour long session and received course credit as compensation for their time. Participants provided written consent prior to starting the experiment. All methods used were approved by The Ohio State University Institutional Review Board.

Stimuli

Displays on each trial consisted of 54 evenly spaced, colored squares (green, red, and blue; sized 1° x 1°) arranged in three concentric rings around a gray fixation cross centered in the middle of the screen (Figure 1A). The inner ring was composed of 12 squares (each centered at 6.3° eccentricity), the middle ring of 18 squares (9.4° eccentricity), and the outer ring of 24 squares (12.4° eccentricity). On every trial there were 14 green squares, 13 red squares, 13 blue squares, and 14 variable squares. These variable squares were either all red on approximately half of the trials or all blue on the other half of the trials. In the center of each square was a gray number between the values 2 and 9 (inclusive). In the green subset the digits in the square were 2 – 9. In the blue and the red subset all squares had values 6 – 9, with the exception of a target square (one in each subset) that had a value 2 – 5. The variable squares had a digit with the value 6 – 9.

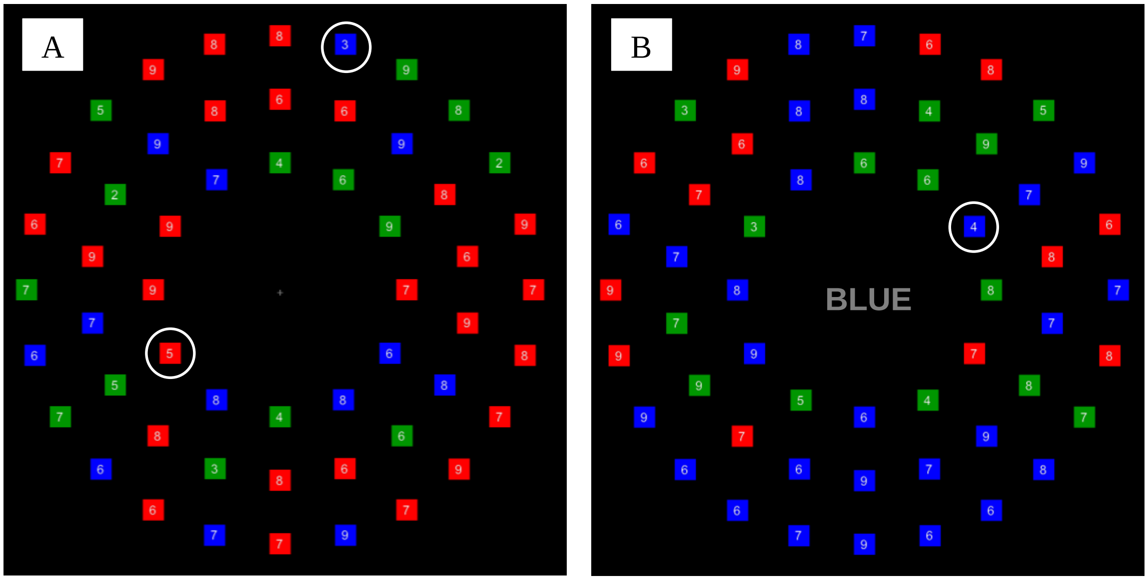

Figure 1 A. An example of the self-directed search ACVS array. Both the blue target (3) and the red target (5) are circled, but the blue target is considered the optimal target as there are half as many blue squares to look through than red squares. **B.** The forced switching ACVS array. The only target (blue 4) is circled. During these trials the participants will be forced to use optimal strategy about 50% of the time. The non-optimal target is the one that must be found in this example.

Design and Procedure

All participants were run in a dimly lit, sound attenuated testing room. A Mac Mini computer and a 24-inch LCD monitor were used to present the stimuli. Participants did not have a fixed head position but were placed approximately 60 cm away from the screen. The experiment was run using MATLAB (Mathworks, Natick, MA, USA), with Psychophysics Toolbox extensions (Brainard, 1997; Pelli, 1997; Kleiner et al., 2007).

Before starting the experiment, each participant was told that there would be search arrays with two targets on each trial: a red square with a number between 2 and 5 inside of it and a blue square with a number between 2 and 5 inside of it. They were told that either target was correct on every trial, so they were free to search for whichever one they chose. They were also told to place either one or two hands on the keyboard (whichever they preferred) and to leave their hand(s) on the keyboard at all times. They were then given ten practice trials before commencing the experiment.

The experiment consisted of six blocks of 84 trials each (504 blocks total) with self-paced breaks between each block. During each break, participants were shown their percentage accuracy on the previous block. The experiment had two parts: 1) a *self-directed search task* with set run lengths and free color choice, and 2) a *forced-switching task* with random run lengths and forced color choice.

Self-directed search task.

The self-directed search task occurred during the first four blocks of the experiment. A fixation cross would appear at the center of the screen for two seconds and then the search array was presented. While the array was on the screen, participants had an unlimited amount of time to search and respond. A participant indicated their response to each trial by pressing a key on the keyboard: V, B, N, M keys (corresponding to the values 2, 3, 4, 5 respectively). Once the participant pressed one of the four keys, the search array disappeared and a new trial began after a 2-second inter-trial interval (ITI). If a response was incorrect (they chose one of the two numbers that were not target numbers) a 400-Hz auditory tone was played for 150 ms during the ITI.

In the self-directed search task, there were two conditions with varied run length. Run length is the number of trials in a row the variable color subset was a particular color. In half of the blocks, the variable color subset changed color on every trial (*Run length 1*). In the other half of the blocks, the variable color subset remained the same for three trials in a row before switching (*Run length 3*). The order of these conditions was counterbalanced across participants.

Forced-switching task.

The forced switching task occurred during the last two blocks of the experiment. Like in the self-directed search task, a fixation cross was displayed for two seconds and then the search array appeared. When the search array was presented, the fixation cross in the center of the screen was replaced with the word RED or BLUE in gray text at the same time as the array (Figure 1B). In these blocks, only one target square was present on every trial instead of two. Participants were instructed to look through the colored subset of the corresponding word to find the one target on every trial. The run lengths were randomly selected between one and six during this task, and the target color was randomly selected for each trial. The rest of the trial was the same as in the self-directed search task.

Results and Discussion

In both run lengths 1 and 3, the search accuracy was near ceiling (M = 98.67% and M = 98.21%, respectively). Accuracy was slightly greater in run length 1 than 3 (paired 2-tailed t-test: $t(49) = 2.566$, $p = 0.013$, $d = 0.286$). In the following analyses, whenever there are comparisons between run length 1 and 3, the data reported are from averaging the two run length 1 blocks together and averaging the two run length 3 blocks together. Additionally, the following analyses exclude trials in which participants were unable to correctly find or report search targets, as well as trials with response times less than 300 ms or greater than three standard deviations above the mean, collapsed across conditions. Furthermore, all switch cost data come from the forced switch version of ACVS and optimal and proportion switch data come from the self-directed search version of ACVS.

Optimality

First, we looked at optimal choice, the main strategy measure previously reported by Irons and Leber (2016, 2018a). We define optimal choice to be when participants chose the square belonging to the smaller colored subset (i.e., the optimal target), and their proportion optimality was how many choices they made relative to all accurate trials. Although we define an optimal strategy, we know that a target choice on any given trial does not necessarily indicate strategy with certainty, as even participants that tend to use optimal strategy may report the non-optimal target opportunistically (e.g., the non-optimal target is near fixation, see Irons and Leber, 2016, 2018a). However, we do find that, overall, choosing the optimal target is considerably more efficient than not, as participants have faster reaction times (see RT results below).

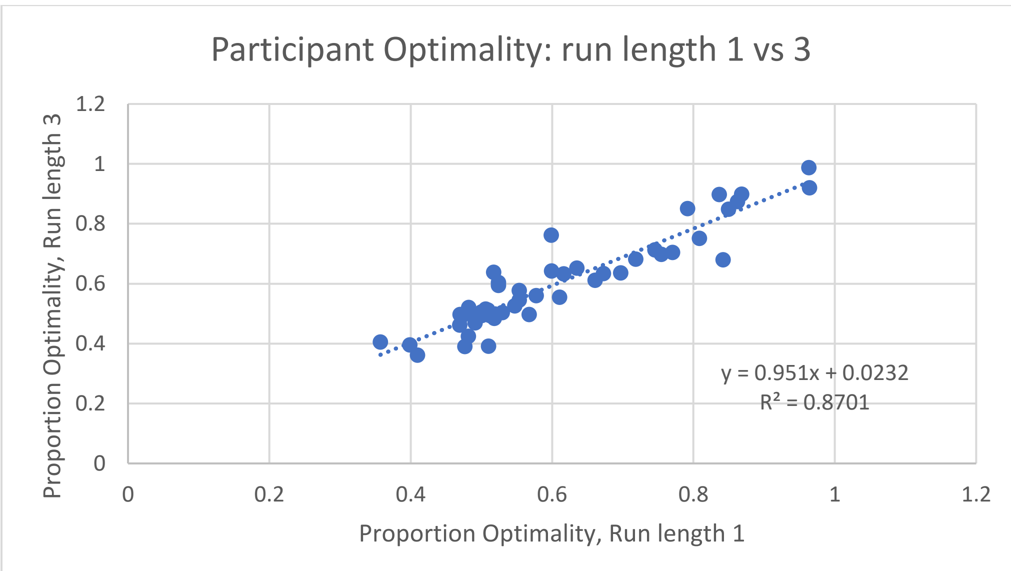

Figure 2 The proportion of a participants' optimal choices during blocks with run length 1 versus blocks with run length 3.

We compared a participant's proportion optimal on blocks with a run length of 1 to that of blocks with a run length of 3, and found no significant difference using a paired 2-tailed t-test ($t(49) = 0.821$, $p = 0.416$, $d = 0.043$, Figure 2). Probing further, we can see that there is a strong correlation between a participant's proportion optimal in blocks with runs of length 1 and 3 ($r = 0.933$, $p < 0.001$). Participants were about 60% optimal on average across all blocks of the self-directed search task (combining blocks with run lengths 1 and 3).

Response Time

Despite the effortful cognitive control that accompanies using the optimal strategy (i.e., constant internal monitoring and target switching), it is associated with a faster reaction time. In this study, participants were significantly faster on trials where they found the optimal target compared to the non-optimal target ($p < 0.001$, Figure 3). We also looked at the average reaction time of participants on blocks of run length 1 versus run length 3 and found no significant difference (RT for run length 1 M = 3627 ms and RT for run length 3 M = 3601 ms, $t(49) = 0.302$, $p = 0.618$, $d = 0.038$). We also calculated the average reaction times of repeat and switch trials to verify the existence of a switch cost in these data. There was a significant difference between repeat and switch trial reaction times (M = 3631 ms and M = 3913 ms, respectively, $t(49) = 4.466$, $p < 0.001$, $d = 0.379$), confirming switch trials had longer reponse times than repeat trials.

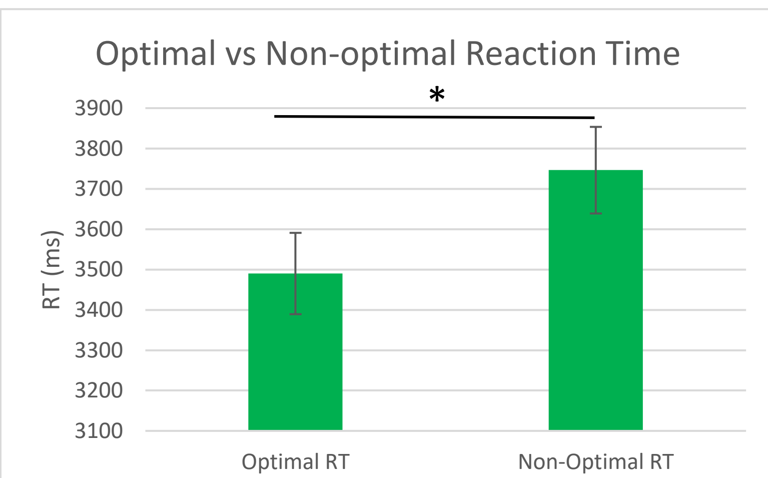

Figure 3 A comparison between reaction times on trials where the optimal target was selected versus when the non-optimal target was selected, $t(49) = 3.725$, $p < 0.001$, $d = 0.348$ (paired, 2-tailed t-test). Optimal RT: M = 3490 ms. Non-optimal RT: 3746 ms. Standard error of the mean bars are also shown.

Proportion of Switching

In the ACVS paradigm, in order to maintain optimality, participants must occasionally switch which colored subset they look through from trial to trial to find the optimal target. If the optimal target color switches frequently, then a participant would have to increase the proportion of switches they make throughout the experiment. On the other hand, if the optimal target color does not switch too often, then maintaining an optimal strategy does not require as frequent switching. We measured this proportion of switches by calculating how often a participant chose a colored target that was different than the previous trial. We compared the proportion of switches on blocks with run length 1 to that of blocks with run length 3 and found a significant difference using a paired 2-tailed t-test (run length 1 M = 0.421, run length 3 M = 0.294, $t(49) = 5.350$, $p < 0.001$, $d = 0.664$). While switching did increase from run length 1 to 3, individuals' proportion switching correlated strongly between blocks with runs of length 1 and 3 ($r = 0.707$, $p < 0.001$, Figure 4).

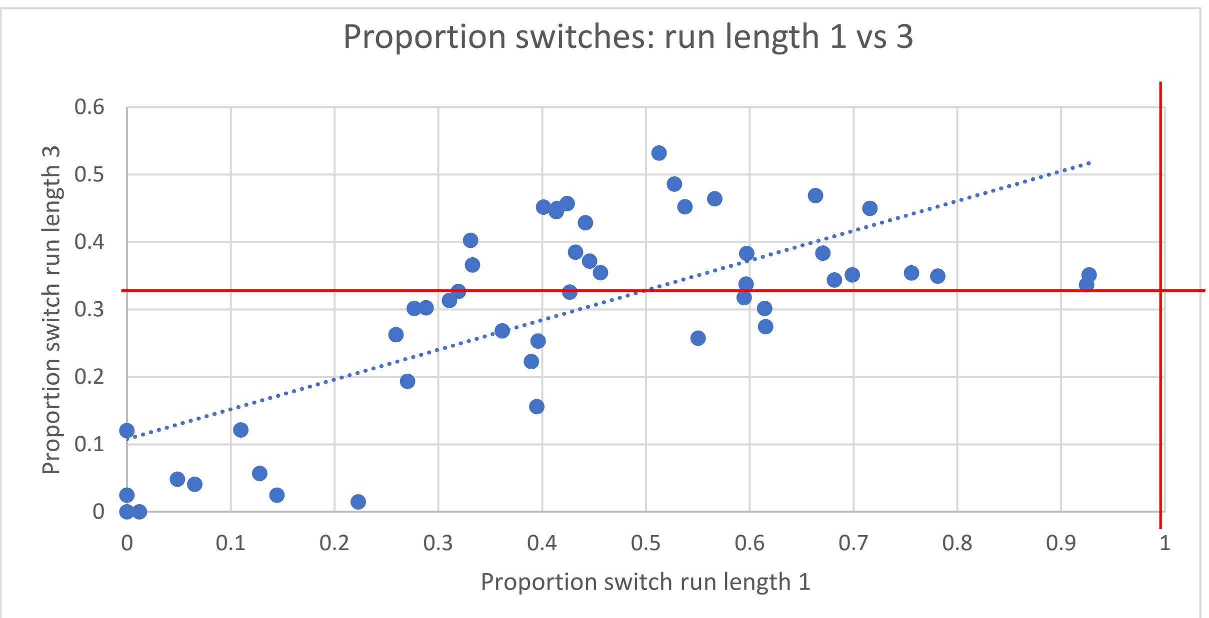

Figure 4 The proportion of switches in blocks with run length 1 vs run length 3. The red lines indicate what proportion of switching is necessary for 100% optimality in each condition: 1.0 during blocks with run length of 1 and 0.325 during blocks with run length 3.

Participants likely increased their switch rates in the run-length 1 blocks compared to run-length 3 blocks because optimal performance would require more frequent switching in the former. Specifically, we calculated the proportion of switches that would be required during the two different conditions (run length 1 and 3) to maintain a perfect optimal strategy. On blocks with run lengths of 1, a person would need to switch 100% of the time, that is, they would have to switch every trial to be 100% optimal. On blocks with run length of 3, a person would need to switch 32.5% of the time to be 100% optimal. Participants, on average, did not switch as much as they needed on blocks with run lengths of 1 to maintain complete optimality (M = 0.421), but they tended to be closer to the necessary rate of switching to be optimal for blocks with run lengths of 3 (M = 0.294). Perhaps there is a point where participants become unwilling to maintain the frequency of switching required to achieve a completely optimal performance.

ACVS Measures and Switch Cost

A switch cost is defined as how much slower a participant is in responding when they choose the target from the opposite color subset versus the same color subset relative to the response color in the previous trial. This switch cost may occur because reconfiguration of an attentional control strategy has long been shown to carry associated reaction time costs (Vickery, King & Jiang, 2005 and Wolfe et al., 2003). We first looked at the relationship between a participant's switch cost (measured by the forced switching task) and their proportion of switches in the self-directed search task, on blocks with run lengths of 1 and 3 (Figure 5). The graph appears to show numerically that participants switched less if their switch cost was higher. This pattern is observable in both blocks with run lengths of 1 ($r = -0.143$, $p = 0.323$) and run lengths of 3 ($r = -0.170$, $p = 0.237$). However, these correlations were not significant.

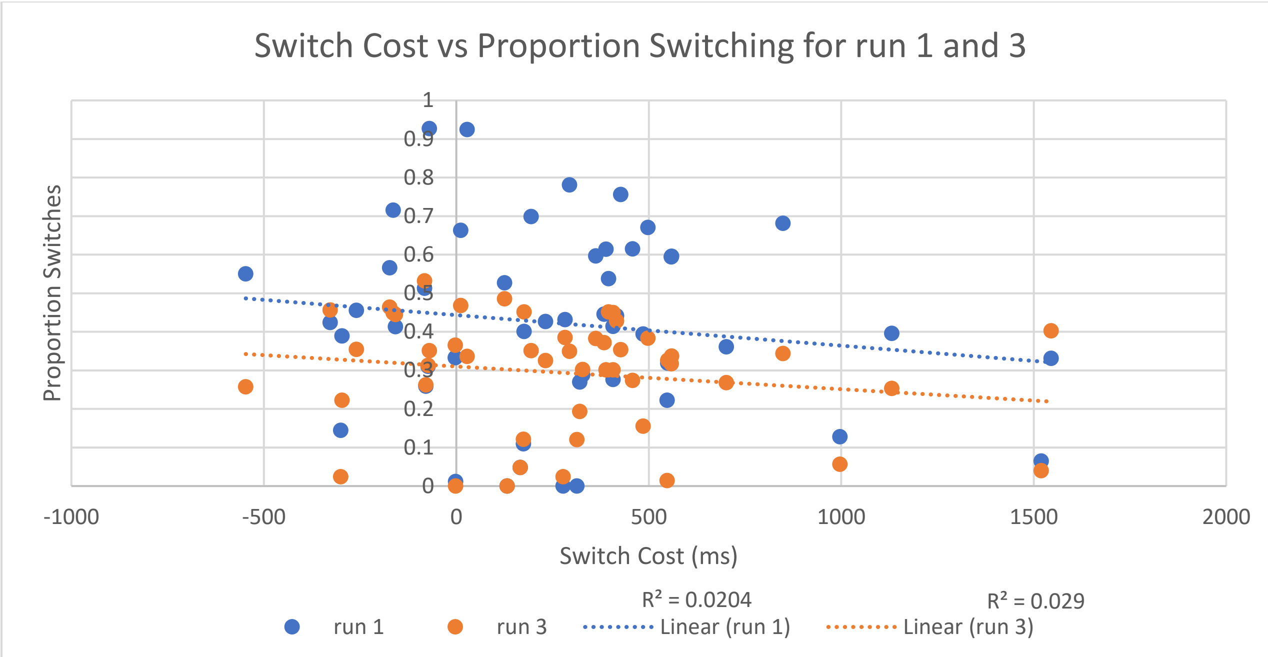

Figure 5 This graph shows the switch cost versus the proportion of switches during blocks of run length 1 (blue) and run length 3 (orange). Both show a negative correlation, an increase in switch cost leads to a decrease in proportion switching, albeit a non-significant one.

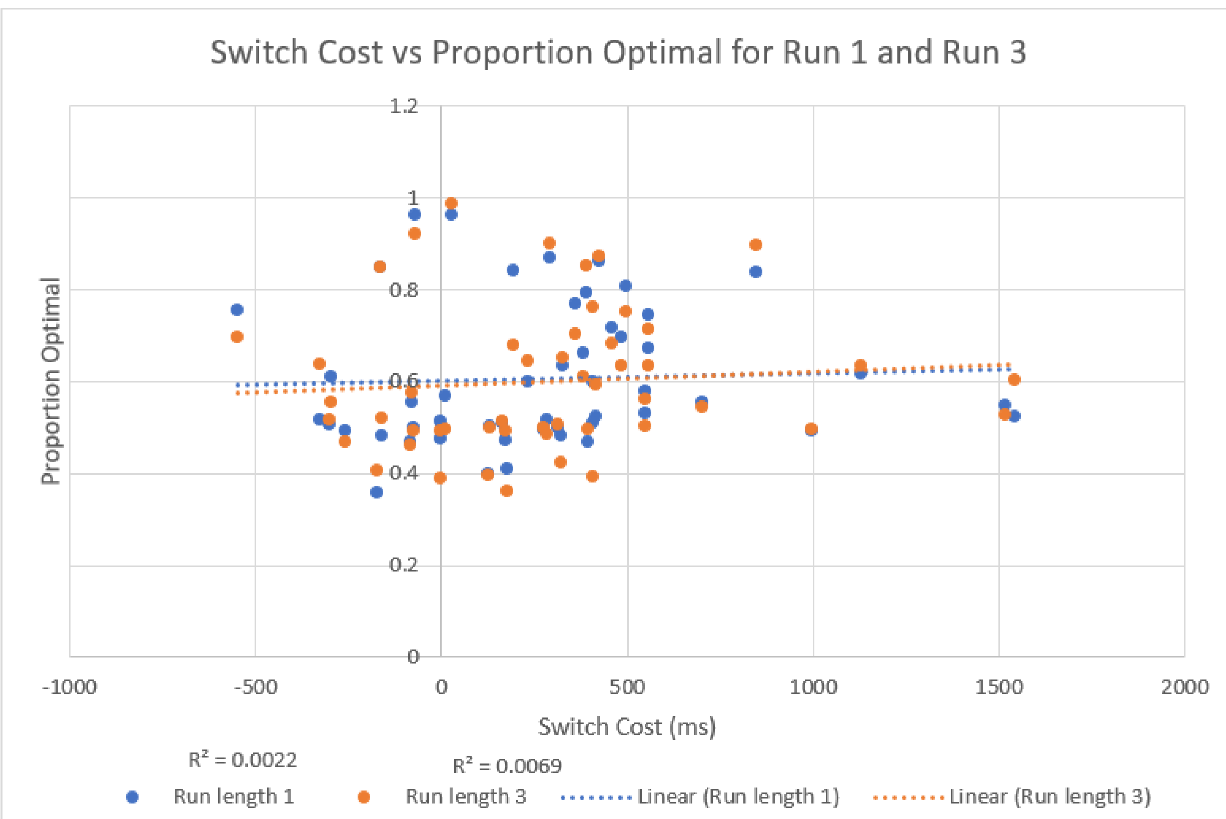

Figure 6 This graph shows the relationship between a participant's switch cost and their proportion optimality on blocks with run lengths of 1 and 3.

Finally, we tested our critical hypothesis on the relationship between switch cost and proportion optimal in blocks with run lengths of 1 and 3. Do lower switch costs, which reflect greater switching ability, relate to proportion optimal target choices? Results failed to reveal a reliable relationship (run 1: $r = 0.047$, $p = 0.746$; run 3: $r = 0.083$, $p = 0.566$; Figure 6).

Conclusion

Does a person's tendency to avoid switching have a relationship with what attentional strategy they choose to employ in a visual search task? Does someone's task switching ability predict how willing they will be to switch? That is, does higher switch cost lead to a decrease in the use of an optimal strategy, as measured by the ACVS paradigm? We defined switch cost as the increase in reaction time a participant experiences when responding to the target belonging to the colored subset that is different than the one they responded to in the previous trial. The optimal strategy was to choose the target belonging to the smaller colored subset. Our hypothesis was that blocks of the experiment with longer run lengths would elicit participants to choose the optimal target more often than blocks with shorter run lengths because they would not have to switch as often. We also predicted that participants with a higher switch cost would use the optimal strategy less. These predictions were based on the assumption that an individual's ability to switch could be measured by looking at their switch cost. For example, someone with a lower switch cost may have a better ability to reconfigure the cognitive settings necessary to task-switching than someone with a higher switch cost. We predicted that the person with the lower switch cost would use the optimal strategy more than the one with a higher switch cost on blocks with shorter run lengths due to this difference in ability to change cognitive control settings.

Our results indicate that there is not an easily discernable relationship between switch cost and optimal strategy use, given the current setup of the paradigm. In other words, we cannot draw any firm conclusions about whether switch cost can predict how much a person will use the optimal strategy. One reason this may be so is that we did not pick run lengths that are distinct enough to elicit a difference in optimal strategy use. In the future, we could have blocks with set run lengths of 1 and 4 or 1 and 6 to see if run lengths that require even less switching to maintain optimal strategy will yield a relationship. Nevertheless, further research will more closely scrutinize this relationship between a person's ability to switch quickly and their use of an optimal visual attention strategy.

Note that others have found a relationship between task switching ability and task choice. Kool and Botvinick (2010) reported that those with a higher switch cost used a demand avoidance strategy (picking the deck with less task switching) more than those with a lower switch cost. So why did our study fail to show such a relationship? One reason may be that the number of subjects Kool and Botvinick used (N = 19) was not a large enough sample size to accurately reveal the presence or lack of a relationship. Moreover, their study differs in significant ways from the one conducted by our lab. Kool and Botvinick asked participants to perform parity or magnitude judgements on digits, whereas we assessed visual attention. Perhaps the differences between these tasks and the discrepancies in finding a relationship between switch cost and strategy use indicate switch costs affect certain cognitive functions to a greater extent than others.

In conclusion, when an optimal visual search strategy is available, people often fail to use it. From our study, we failed to find a relationship between a person's ability to task switch and their use of the optimal search strategy. Future studies will need to be conducted to better elucidate why such a vast quantity of individual differences in strategy use exists.

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